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Comparison of Implementation in Blood Cancer Causes and Diseases

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ABSTRACT

Blood malignancies are extremely dangerous for human life. Early and accurate detection is essential for efficient treatment and improved patient outcomes. Traditional diagnostic methods can be subjective and time-consuming. Delays in diagnosis can lead to life-threatening complications, as some blood cancers progress rapidly.

This work explores the transformative potential of Machine Learning (ML) and Deep Learning (DL) in blood cancer detection. Support Vector Machine (SVM) and other machine learning methods and K Nearest Neighbour (KNN) analyze blood cell images and identify cancerous cell features, achieving high accuracy in leukemia detection. This allows for faster and more objective diagnoses, potentially leading to earlier interventions and improved patient outcomes. Deep Learning approaches, particularly Convolutional Neural Networks (CNNs), hold even greater promise. The requirement for manual feature extraction is eliminated by CNNs' ability to automatically learn features from images.

The integration of ML and DL significantly improves blood cancer detection accuracy and efficiency. This paves the way for earlier diagnoses, improved patient care, and ultimately, saving lives. This work concludes by pointing forth possible directions for more study, such as improving these methods even more.

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1. INTRODUCTION

Blood cancer, also known as hematological malignancy, encompasses a group of cancers that affect the blood, bone marrow, and lymphatic system. These cancers arise from various types of blood cells and can be classified into three main types: leukemia, lymphoma, and myeloma. Leukemia is characterized by the fast synthesis of abberant white blood cells , which eventually crowd out healthy cells in the bone marrow. Lymphoma affects the lymphatic system, which is essential for the body's immune response, while myeloma impacts the plasma cells that are in charge of producing antibodies. Early detection of blood cancer is crucial for initiating timely and appropriate treatment, which significantly impacts patient outcomes.

Blood cancer diagnosis has been transformed by recent developments in medical imaging, machine learning, and deep learning techniques. These technologies have enabled researchers to develop more accurate and efficient methods for diagnosing blood cancer, leading to improved patient outcomes. For example, machine learning algorithms like Support Vector Machine (SVM) and

K Nearest Neighbour (KNN) classifiers have been used to develop robust frameworks for leukemia detection, achieving notable accuracies. These algorithms integrate thorough image pre-processing techniques and segmentation methodologies to extract essential cellular features crucial for accurate diagnosis. Furthermore, the integration of advanced methods for processing images using machine learning algorithms has not only enhanced diagnostic precision but also prepare the ground for upcoming studies in sub classification of leukemia subtypes and the evolution of personalized diagnostic tools.

The need is increasing for effective blood cancer detection methods because of the increasing prevalence of the disease. Traditional diagnostic approaches, such as manual cell counting and the risk of overfitting in image processing techniques, pose significant challenges. In order to tackle these issues, scholars have suggested methodologies that incorporate machine learning techniques with advanced image processing methods. These methodologies aim to enhance the accuracy and efficiency of blood cancer detection by leveraging algorithms like Effective Fuzzy C Means (EFCM) and Iterative Morphological Process (IMP). By employing these advanced techniques, researchers are paving the way for faster, more cost-effective, and safer diagnostic procedures for improved patient outcomes.

Depending on the disease's kind and stage, blood cancer can appear with a variety of symptoms. Symptoms often include inexplicable weight loss, fatigue, easy bruising or bleeding, frequent infections, swollen lymph nodes, and bone pain. These symptoms can often be vague and nonspecific, making diagnosis challenging. However, early detection of blood cancer is essential for enhancing patient results, highlighting the importance of developing accurate and efficient diagnostic methods.

2. Literature Survey

The proposed methodology for blood cancer detection, as delineated by Saranya et al. (2021), Paper [1] highlights the significant role of machine learning and image processing in early disease detection. By employing SVM in paper [18]and K Nearest Neighbour (KNN) classifiers, the authors present a robust framework for leukemia detection with notable accuracies of 97% and 91%, respectively. This approach, expounded upon in the work by Saranya et al., integrates thorough pre-processing techniques like median filtering and histogram equalization to enhance image quality and contrast. Following these steps, segmentation methodologies such as watershed segmentation and K-means clustering facilitate the extraction of essential cellular features crucial for accurate diagnosis. The authors' meticulous attention to extraction of feature and classification algorithms underscores the machine learning’s potential in transforming cancer diagnostics, offering an encouraging path toward early identification and treatment.

The literature survey in Paper [2] highlights how the rising incidence of blood cancer necessitates the development of efficient diagnostic techniques. The proposed methodology outlined in Paper [2] embides machine learning techniques with advanced image processing methods to address the shortcomings of traditional diagnostic approaches. By leveraging algorithms like Effective Fuzzy C Means (EFCM) and Iterative Morphological Process (IMP), the authors aim to enhance the precision and effectiveness of blood cancer detection. Their approach encompasses pre-processing and segmentation of blood cell images, followed by feature extraction and classification. Through empirical evaluation, the authors demonstrate the superiority of their ensemble model, showcasing a significant improvement in accuracy compared to conventional algorithms. This comprehensive methodology promises to revolutionize blood cancer diagnosis, offering faster, more cost-effective, and safer diagnostic procedures for improved patient outcomes.

Paper [3] [19] delves into blood cancer detection and cardio vascular diseases, highlighting the crucial need for early and accurate diagnosis. They focus on deep learning techniques, exploring various architectures and frameworks used in blood cancer research. The authors tackle the difficulties presented by diverse forms of blood cancer, cardio vascular diseases and stress the importance Using deep learning methods for automated identification in medical image analysis .The paper also discusses common symptoms and diagnostic procedures, illustrating the diverse manifestations of blood cancer symptoms and detailing types of blood cancer, each with distinct features and diagnostic challenges. By examining the restrictions of traditional diagnostics and the potential of deep learning, the study advocates for advancements in data collection, preprocessing, and model development, emphasizing integration with clinical workflows and ensuring ethical considerations, generalizability, and interpretability of deep learning models in blood cancer detection.

Paper [4] highlights the critical need for automated techniques in blood cancer detection, showcasing the possibility of deep learning techniques. The study achieves over 95% accuracy in identifying blood cell abnormalities using a Hybrid Ensemble Deep Learning approach, combining Multi-Layer Perceptron (MLP) and Convolutional Neural Network (CNN) models. It successfully detects various blood cancer types, including acute lymphocytic, myeloid, and chronic leukemia. Additionally, the research emphasizes the importance of transfer learning strategies, such as the Google Net deep transfer architecture, in differentiating between normal and cancerous blood cells, showcasing advancements in deep learning-based disease detection. Paper [4] gives a thorough summary of existing research in blood cancer detection, discussing various approaches, including white blood cell segmentation, machine learning, and deep learning algorithms for classification. The survey highlights the significance of interdisciplinary research in advancing blood cancer detection and suggests future research directions, emphasizing innovative deep learning models which are required incorporated into clinical procedures for improved disease detection and personalized treatment strategies.

The study conducted by Mosayebi et al. (2019) in Paper [5] extensively explores the use of mobile nano sensors (MNSs) for early cancer detection within blood vessels. The authors model the movement of MNSs, considering factors such as advection and diffusion, and propose deterministic measurement positions along the x-axis. They develop a comprehensive framework for modeling the activation levels of MNSs based on encountered biomarker concentrations, incorporating contributions from both cancerous and healthy cells. The study proposes two detectors: an optimal Neyman-Pearson Likelihood Ratio Test (LRT) and a simpler Sum Detector. Through simulations, the study validates the proposed models and evaluates the detectors against a benchmark scheme where nanosensors are fixed at the detection site. The results indicate that both detectors outperform the benchmark scheme, showcasing the potential of MNS-based approaches for early cancer detection (Mosayebi et al., 2019).

The field of computer-aided diagnosis (CAD) has witnessed significant advancements, particularly in the context of leukemia detection using Convolutional Neural Networks (CNNs). Paper [6] present a pioneering study focusing on the automated identification of white blood malignancy using microscopic pictures of bone marrow. Their research leverages a CNN model trained on the SN-AM dataset, achieving an impressive accuracy rate of 97.2%. Through the use of CNNs and other deep learning approaches, the study demonstrates the potential of machine learning algorithms in revolutionizing medical diagnostics, particularly in relation to the identification of leukemia, providing a more efficient and accurate approach compared to traditional methods.

Furthermore, the proposed CNN architecture in Paper [6], comprising five convolutional layers and four fully connected layers, illustrates how well deep learning works in image recognition and classification tasks. The capacity of the model to precise information from cell images and accurately identify leukemia subtypes underscores the significance of CNNs in enhancing patient outcomes. The study's findings not only showcase the capabilities of CNNs in medical imaging but also clear the path for the future research in leveraging deep learning for automated disease detection and diagnosis.

The Paper [7] reviews methods for detecting blood cancer, focusing on Acute Lymphoblastic Leukemia (ALL), using image processing. It emphasizes the requirement for precise and efficient detection due to the rapid progression of leukemia. Various techniques like image segmentation, morphological analysis, and feature extraction are talked about, each with its advantages and limitations. The research proposes a methodology involving image gathering, improving, dividing, extracting features, and classifying Challenges such as cell deformation and overlapping are noted, underscoring the need for automated systems. The paper concludes that treatment can be enhanced by early discovery outcomes.

In Paper [8] Putzu work for leukocyte characterization using microscopic blood images, reaching a precise of 93.2% in leukemia identification with kernel SVM under ten-fold cross-validation. Abbas and Khashman used Otsu's thresholding, median filtering, and canny edge detection for leukemia classification, achieving encouraging results. Madhukar demonstrated a 93.5% accuracy rate in ALL classification using SVM with cross-validation, focusing on nucleus clustering and feature extraction. Piuri and Scotti combined edge detection and morphological methods for membrane detection in white cells. Various clustering techniques, including fuzzy clustering methods, K-means, and others have been working for nucleus location in leukemia cells.

Paper [9] highlights the importance of automated detection methods for white blood cell cancer, particularly leukemia, due to its critical nature and the need for accurate and timely diagnosis. Several image processing methods, such as segmentation and classification algorithms, have been investigated in earlier research , to differentiate between normal and cancerous cells. These investigations have demonstrated encouraging outcomes with deep learning models like CNNs and FCNNs, which are adept at handling complex image data. Additionally, the use of optimization algorithms such as SSA and SESSA has further enhanced the performance of these models, leading to improved accuracy in detecting leukemia cells. Authors of paper[20] have done enhancement to control the output voltage level. Overall, these advancements in machine learning and image processing techniques offer valuable tools for medical professionals in diagnosing and treating blood cancers more effectively.

Paper [10] suggests an automated technique for classifying leukocytes in microscopic images to detect leukemia, utilizing share-based features, linear contrast stretching, histogram equalization, and K-means transformation . Implemented in MATLAB, the model aims to detect leukemia cells in healthy blood cells without requiring expertise, focusing on automation. Highlighting the importance of early leukemia detection for appropriate treatment, the paper discusses manual detection challenges, emphasizing the benefits of automated techniques for quick and accurate results. The proposed system aims to improve image differentiation and segmentation of white blood cells (WBCs) and nuclei, crucial for accurate leukemia detection, and to develop fresh attributes for for enhanced accuracy. The research suggests that the suggested approach might greatly enhance accuracy and efficiency, with potential applications in detecting various diseases using microscopic images. In Paper [21] author does study on fetus status using photoplethysmograph signals.

3. TYPES OF BLOOD CANCER

Primarily, there are three fundamental kinds of blood cancer. Each of the variety may also include several variations, but in general this cancer is categorized into the following kinds

A. LEUKEMIA

Leukemia is a type of cancer of the blood cells. White blood cells are a component of the blood. They help the body to fight against infections. When someone has an infection with leukemia, the DNA in the cells mutate in such a way that immature white blood cells are formed in large number in the body. These cells are called blasts. Leukemia can affect different cells of the blood and the classification of disease is done in four types in the manner they infect. The disease progresses when these aberrant cells progressively replace the bone marrow's function.

Type of leukemia	Description	Causes
Acute lymphocytic lymphoma (ALL)	This type of leukemia affects the lymphocytes. A large number of immature lymphocytes are produced and they hinder the functioning of the bone marrow.	Though the exact cause is not known, exposure to toxins like benzene and radiation, chemotherapy and chromosomal abnormality can increase the risk of ALL.
Acute mylogenous leukemia (AML)	This cancer develops from inside the bone marrow involving immature cells that would have turned to white blood cells.	It is caused by exposure to harmful chemicals and rays, blood disorders or weakened immune system. It is most common type and the disease progresses rapidly.
Chronic lymphocytic leukemia (CLL)	It is a slow increase in lymphocytes affecting the lymph nodes and the spleen. Ultimately it causes the bone marrow to stop functioning.	The reason is not known and it is not linked to radiation. However, exposure to Agent Orange during Vietnam war increased the risk of CLL.
Chronic mylogenous leukemia (CML)	It is a slow build up of immature white blood cells hampering the function of the bone marrow.	CML is related to the presence of an abnormal chromosome called Philadelphia chromosome. Radiation exposure may also be a cause.

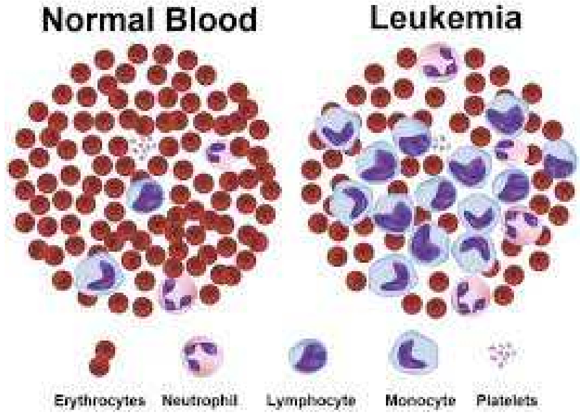


Fig 4.1: Feature difference between normal blood cell and white cancer blood cell

B. LYMPHOMA

Lymphoma is a type of blood cancer where lymphocyte – growth of a component of the blood happens at an abnormal rate. They are often present as a solid tumor in certain sections of the body like lymph nodes, bone marrow, spleen etc. In most cases, the causes are not known. The common symptoms include fever, chills, fatigue, pain in lymph nodes and other specific areas of the body. Chemotherapy, radiation therapy and bone marrow transplantation are the most common treatment options for lymphoma. B or T lymphocytes are a component of the blood. They help the body to fight against infections and form a part of the immune system. They are found in the lymph tissue which forms the lymphatic glands. Lymphoma is a type of cancer of the blood that affects the lymph nodes. The result is that the lymphocytes begin to behave in an abnormal manner. They also multiply rapidly and prevent normal cells from being formed till they overwhelm the system. However, with timely intervention, certain types of lymphomas can be cured completely.

Name	Description	Causes
Hodgkin lymphoma	It is the cancer of the lymph tissue found in spleen, lymph nodes, bone marrow etc.	The cause is unknown. Prior infection with HIV or Epstein Barr virus is seen to increase the risk of this disease.
Non Hodgkin lymphoma	It is the cancer of the B lymphocytes found in lymph tissues	The cause is unknown. The disease mostly develops in people with weakened immune system. Prior HIV infection or organ transplantation increases the risk.
Burkitt lymphoma	It is a rare type of disease mostly observed in African children. It is common in males.	In Africa, it is linked to the Epstein Barr virus, but no such link has been found in the USA. Weakened immune system increases the risk

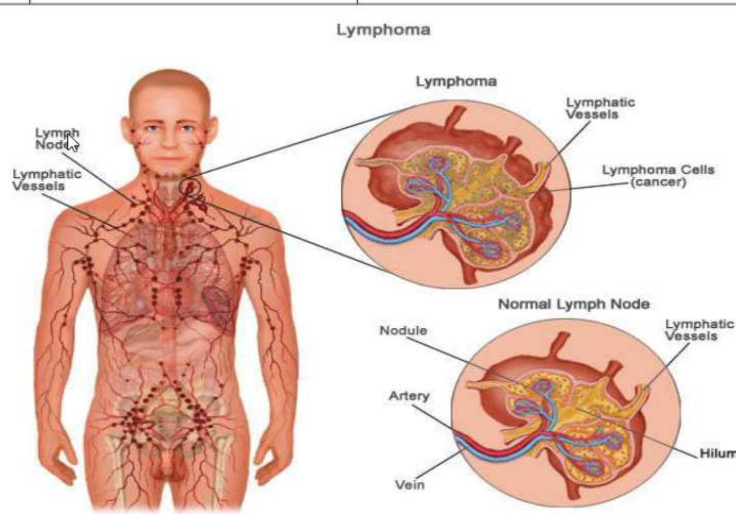


Fig 4.2: Lymphoma in human body

C. MYELOMA

The bone marrow's plasma cells produce antibodies and help immune system to fight against outside aggression. Myeloma is a cancer that affects these plasma cells. They begin to behave abnormally and form tumors outside the solid bone. This gradually weakens the bones. It also does not allow the bone marrow to produce healthy blood cells. The cause of the disease is not clearly known.

The blood cells in the human body are formed in the soft spongy tissue of the bone marrow. One of the cells which are produced here is the B lymphocytes or the plasma cells. These cells help to produce antibodies in the blood. The antibodies are the chief soldiers of the immune system of the body. When myeloma occurs, these plasma cells begin to behave abnormally. They multiply rapidly and eventually they form tumors on the surface of the solid bones. This attacks the bones so that it can no longer function properly. Moreover, the abnormal plasma cells interfere with the ability of the bone marrow to produce healthy blood cells. The abnormal plasma cells often produce an antibody called paraprotein which affects the kidney function negatively. The bone function is also hampered resulting in abnormally high calcium levels or hypercalcemia. Myeloma is also known as plasma cell myeloma or Kahler's disease.

Causes of Myeloma: The exact cause of myeloma is unknown. There are some research suggesting and longtime exposures to certain harmful chemicals or radiation can cause myeloma. However, many cases are reported where no such exposure is recorded. In such cases, it has not been possible to determine the causative factors.

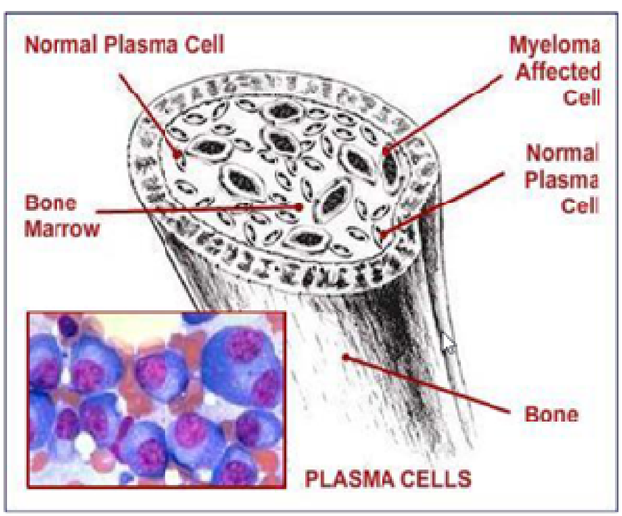


Fig 4.3: Myeloma in human body

4. Methodology

A. Blood Cancer Detection using ML

The works objective is to compare the image processing techniques to get the accurate result for detection of leukemia with good accuracy. The exact count of cells determines the early detection of leukemia. In medicine field, Complete Blood Count (CBC) plays a major role. It determines the normal and sufficient or required blood count for humans. Microscopic images which are extracted from the database that serves as the leukemia detection process's input image. These images undergo pre-processing techniques to make the images free from noises. After pre-processing, thresholding is done to increase the contrast of an image. The particular cells from the input image are separated using a segmentation process. In feature extraction, many features are calculated to find the differences among infected and non-infected blood cells. Finally, classification techniques like SVM and KNN are used for classification of the type of cancer, if cancer is detected.

The overview of the work is given as a flow. First, we have to get the input image. After that pre-processing is carried out this removes the unwanted noises present in the image. Image Segmentation and feature extraction is done. Finally, classification takes place which gives the accuracy, sensitivity, error rate and specificity with the help of confusion matrices.

The methodology flow involves several key steps:

1. Image Acquisition: Blood cell images are captured from a microscope, typically from a database like TCIA.
2. Pre-processing: Techniques like median filtering and histogram equalization are applied to improve image quality and contrast.
3. Segmentation: Cells are separated from the background using methods like Otsu's and HSV equalization thresholding, watershed segmentation, and K-means clustering.
4. Feature Extraction: Feature extraction is a reduction process in which the original image is taken as raw data and it is divided into many valuable data forms. Geometrical, statistical, and textural features of the cells are calculated to describe their characteristics.

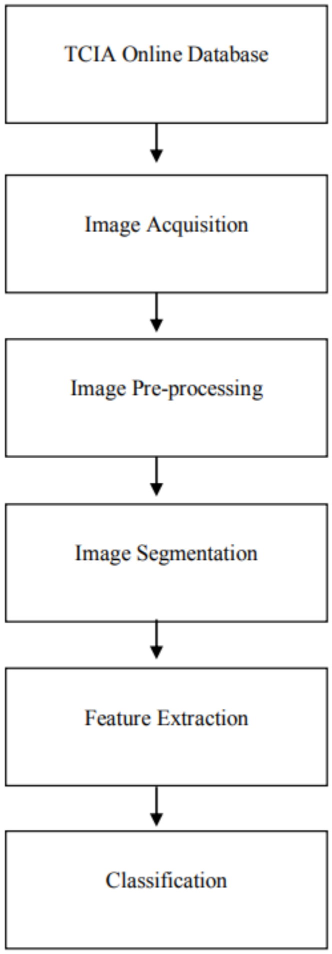


Fig 5.1: Flowchart Of the methodology

The proposed methodology demonstrates promising results in the detection of leukemia from blood smear images. By using sophisticated image processing methods and machine learning algorithms, the study achieves high accuracy in classifying leukemia cells. Specifically, the SVM classifier achieves an accuracy of 97%, indicating its effectiveness in differentiating leukemia-infected cells from normal cells . The KNN classifier also performs well, achieving an precision of 91%.

Moreover, the methodology provides detailed insights into the performance of the classifiers through various metrics such as specificity, sensitivity, F1 score, and error rate. These metrics help in evaluating the robustness and dependability of the categorization models. The confusion matrix, which summarizes the classification results, further enhances the understanding of the classifiers' performance.

B. Convolutional neural networks are used to automatically detect white blood cancer from bone marrow microscopic pictures.

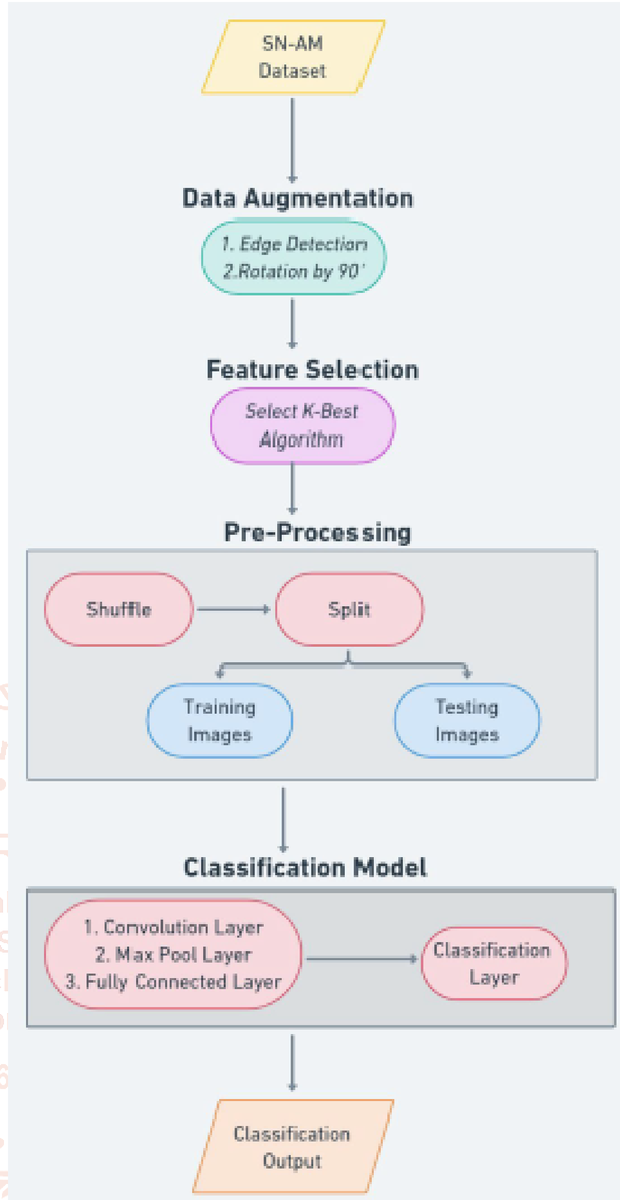
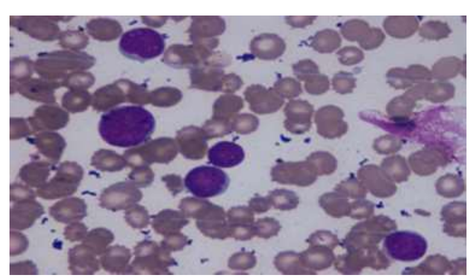


Fig 5.2: Flowchart of the proposed methodology

A. Dataset Description:

The study's dataset is essential for both training and evaluating the suggested convolutional neural network (CNN) model. It comprises two subsets: one containing images of patients diagnosed with B-Lineage Acute Lymphoblastic Leukemia (BALL), totaling 90 images, and the other containing images of patients diagnosed with Multiple Myeloma (MM), totaling 100 images. These images are high-resolution, with dimensions of 2560x1920 pixels, and are stored in BMP format.



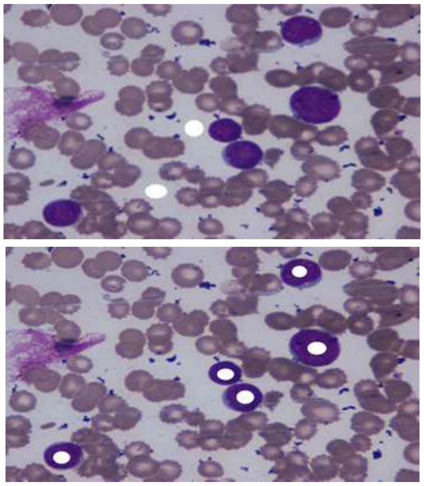


Fig 5.3: Sample images of ALL Dataset. (a) ALL sample image, (b) ALL background mask, (c) ALL nucleus mask. ALL indicates acute lymphoblastic leukemia.

B. Data Augmentation:

Data augmentation is a key step to enhance the robustness of the CNN model. Two main techniques are employed: rotation and edge extraction. Rotation helps the model learn to recognize cancer cells from different angles, improving its ability to generalize to unseen data. Edge extraction highlights the boundaries of objects in the images, providing additional information for classification.

C. Feature Selection:

Feature selection is critical for reducing the dimensionality of the dataset and selecting the most relevant features for classification. Here univariate feature selection is used, specifically the Chi-square test. This test evaluates the independence of features from the target variable, selecting those that contribute the most to the classification task. This step helps improve the model's performance by focusing on the most informative features.

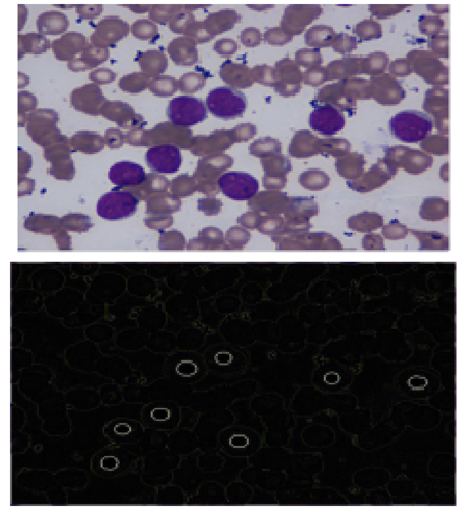


Fig 5.4: Data augmentation of microscopic images. (a) ALL original image rotated by 90 degrees anticlockwise(b) Detected Edges of the original ALL image

D. Pre-processing of Images:

Preparing the dataset for CNN model training requires pre-processing. This step involves normalizing the images and splitting them into testing and training sets. By ensuring that every image has a consistent scale, normalization improves the model's learning capabilitiy . The dataset is then divided into a 75% training set and a 25% testing set.

E. Proposed Convolution Neural Network and Architecture:

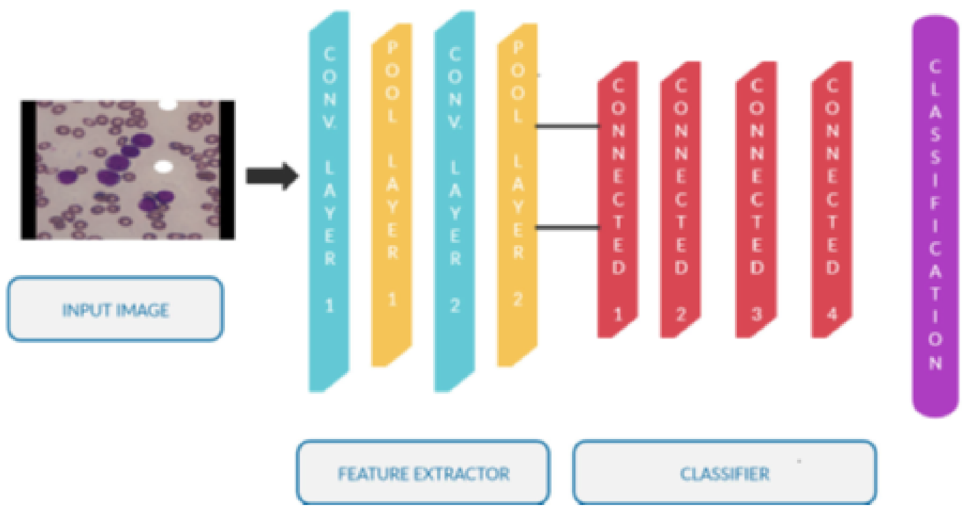


Fig 5.5: Proposed CNN model architecture.

The design of CNN model architecture is to classify white blood cancer types (ALL or MM) accurately. Convolutional layers for feature extraction are among its many layers , max-pooling layers for down-sampling, and fully connected layers for classification. The model takes an image as input and outputs the predicted cancer type. The architecture includes two convolution layers with softmax activation functions, followed by a pooling layer. Additionally, there are five fully connected layers with softmax activation functions and a final output layer with a sigmoid activation function.

5. CONCLUSION

The combination of machine learning (ML) and deep learning approaches has led to notable progress in the detection and categorization of blood cancer in recent years. ML algorithms discussed above have played a crucial role in processing large datasets and identifying patterns that aid in accurate diagnosis. These algorithms have improved the accuracy and efficency of blood cancer detection, leading to more timely and effective treatments.

DL a subset of ML, has further revolutionized blood cancer detection through its ability to automatically learn features from images. Convolutional Neural Networks (CNNs) have been particularly effective in analyzing medical images like blood smears, eliminating the need for manual feature extraction.

The combination of ML and deep learning techniques has enabled healthcare professionals to detect and classify various types of blood cancers, including leukemia, with unprecedented accuracy. Early detection facilitated by these technologies has led to improved patient outcomes and more personalized treatment strategies. Despite the challenges of data availability and model interpretability, the future holds great promise for the continued advancement of ML and deep learning in blood cancer detection and classification, ultimately leading to more effective diagnostic and treatment approaches.

6. Scope for Future

The future scope of blood cancer detection and classification using machine learning (ML) and deep learning techniques is incredibly promising. One area of focus is the development of more robust and interpretable deep learning models. Researchers are working towards creating models that not only achieve high accuracy but also provide clear explanations of their predictions. This would increase the acceptability and credibility of deep learning systems in clinical settings, leading to more widespread adoption and improved patient care.

Future studies will concentrate on resolving data-related issues availability and clinical validation. Efforts are underway to expand and diversify datasets, particularly for uncommon blood cancer subtypes, to improve the performance and generalizability of ML and deep learning models. In order to integrate these models into ordinary clinical practice and make sure they meet the strict requirements needed for use in actual healthcare settings, clinical validation will be essential.

Overall, the future of blood cancer detection using ML and deep learning is bright, with ongoing research poised to significantly improve diagnostic accuracy and patient outcomes.

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